Aalto University
School of Business

EFFECTS OF JOB LOSS ON ICT SECTOR EMPLOYEES' LABOR MARKET OUTCOMES

Master's Thesis

Eeva Hietamäki
Aalto University School of Business
Department of Economics
Spring 2018

Aalto University
School of Business

Aalto University, P.O. BOX 11000, 00076 AALTO
www.aalto.fi

Abstract of master's thesis

Author Eeva Hietamäki

Title of thesis Effects of Job Loss on ICT Sector Employees' Labor Market Outcomes

Degree Master of Science in Economics and Business Administration

Degree programme Economics

Thesis advisor(s) Manuel Bagues

Year of approval 2018 **Number of pages** 34 **Language** English

Abstract

I study the causal effect of job loss on ICT workers' employment level, earnings, probability of becoming an entrepreneur and probability of leaving the ICT sector. Previous research is unanimous with the finding that job loss has several negative and persistent effects not only on individuals' future employment and income, but also on health and fertility. This thesis contributes to the previous literature by focusing on the most recent years and sector-specific effects. ICT sector is a relatively large employer in Finland compared to other OECD countries, and during the past years it has also become a large source of lay-offs.

My thesis examines the workers who lost their job due to a plant closure or a mass lay-off, and compares them with labor market outcomes experienced by workers who were not impacted by plant closure or mass-layoff, but who are similar by observable characteristics. As the effects might vary over time, I study the effects experienced after job loss during four different time periods: 2009-2011, 2005-2007, 1998-2000 and 1991-1993.

I find that in general, there are no systematic differences in effects of job loss between ICT and non-ICT workers. One year after job loss, displaced ICT workers experience 5.2-14.4 percentage points lower employment level compared to their counterparts, while displaced non-ICT workers experience 3.3-23.0 percentage points lower employment level compared to their counterparts. The effect varies greatly between time periods; job loss during the recession period of 1991-1993 has the most severe effects, while other three periods are rather similar to each other. In terms of the effect on income, my results suggest that displaced ICT workers experience 3.2-15.0% lower income one year after displacement, while displaced non-ICT workers experience 7.1-12.7% lower income, compared to their counterparts. When comparing the differences in earned income, ICT and non-ICT workers differ more. However, the evidence across time periods is mixed, suggesting larger losses for ICT workers during the three most recent periods.

All displaced workers have rather small increase of 0.1-0.7 percentage points in the probability of becoming an entrepreneur followed by displacement. I find no statistically significant differences between displaced ICT and displaced non-ICT workers. Lastly, job loss decreases the probability of staying in the ICT sector by 9.8 percentage points during the most recent observation period, when differences in employment level have been taken into account. During more recent periods, displaced workers seem to be more prone of leaving the sector, but they are also more likely to return than workers displaced during earlier time periods.

Keywords job loss, ICT sector

Aalto-yliopisto
Kauppakorkeakoulu

Aalto-yliopisto, PL 11000, 00076 AALTO
www.aalto.fi

Maisterintutkinnon tutkielman tiivistelmä

Tekijä Eeva Hietamäki		
Työn nimi Irtisanomisten vaikutukset ICT-alan työntekijöiden työmarkkinatuloksiin		
Tutkinto Kauppatieteiden maisteri		
Koulutusohjelma Taloustiede		
Työn ohjaaja(t) Manuel Bagues		
Hyväksymisvuosi 2018	**Sivumäärä** 34	**Kieli** Englanti

Tiivistelmä

Tämä tutkielma selvittää irtisanomisten vaikutuksia ICT-alan työntekijöiden työllisyysasteeseen, ansiotuloihin, todennäköisyyteen ryhtyä yrittäjäksi sekä todennäköisyyteen poistua ICT-sektorilta. Aiemmassa taloustieteellisessä tutkimuksessa irtisanomisella on todettu olevan pitkäkestoisia negatiivisia vaikutuksia työllisyyteen ja tuloihin, sekä myös terveyteen ja hedelmällisyyteen. Tämä tutkielma täydentää aiempaa tutkimusta keskittymällä viime vuosiin sekä sektorikohtaisiin vaikutuksiin. ICT-sektori on Suomessa kansainvälisesti vertailtuna varsin suuri työllistäjä, joka on viime vuosina ollut suurten irtisanomisten lähde esimerkiksi Nokian ja Microsoftin vastoinkäymisten vuoksi.

Tutkin kausaalista vaikutusta vuosi- ja sektorikohtaisesti seuraamalla toimipaikan sulkemisen tai massairtisanomisten seurauksena irtisanottuja henkilöitä. Vertaan irtisanottujen henkilöiden työmarkkinatuloksia havaittavilta ominaisuuksiltaan samanlaisten, mutta ei edellä mainituin perustein irtisanomisen kohteeksi joutuneiden henkilöiden työmarkkinatuloksiin. Sillä vaikutukset eri ajanjaksoina saattavat erota suurestikin, keskityn irtisanomiseen neljän seuraavan ajanjakson aikana: 2009-2011, 2005-2007, 1998-2000 sekä 1991-1993.

Yleisesti työmarkkinavaikutuksissa ei ole havaittavissa systemaattisia eroavaisuuksia irtisanottujen ICT-työntekijöiden ja muiden irtisanottujen työntekijöiden kohdalla. Vuoden kuluttua irtisanomisesta, irtisanottujen ICT-työntekijöiden työllisyysaste on 5.2-14.4 prosenttiyksikköä vertailuryhmää matalampi, kun samat luvut muiden irtisanottujen henkilöiden kohdalla ovat 3.3.-23.0 prosenttiyksikköä. Vaikutukset ovat suurimmillaan henkilöillä, jotka tulivat irtisanotuiksi 1991-1993 laman aikana. Irtisanottujen ICT-työntekijöiden ansiotulot ovat 3.2-15% vertailuryhmää matalammat vuosi irtisanomisen jälkeen, kun taas vastaavat luvut muille irtisanotuille ovat 7.1-12.7%. Ansiotulovaikutusten suhteen irtisanotut ICT-työntekijät eroavat enemmän muista irtisanotuista; tulosteni mukaan irtisanotut ICT-työntekijät kärsivät irtisanomisesta enemmän kaikilla kolmella tuoreimmalla aikaperiodilla.

Irtisanominen ei juurikaan nosta henkilöiden todennäköisyyttä ryhtyä yrittäjäksi. Todennäköisyys kasvaa vain hieman, noin 0.1-0.7 prosenttiyksikköä. Viimeisimpänä, irtisanominen laskee todennäköisyyttä jatkaa työskentelyä ICT-sektorilla 9.8 prosenttiyksiköllä, kun erot työllisyysasteissa on huomioitu. Tuoreimpina vuosina irtisanotut henkilöt ovat olleet hanakampia poistumaan ICT sektorilta työnmenetyksen jälkeen, mutta he ovat myös todennäköisemmin lopulta palanneet takaisin.

Avainsanat irtisanomiset, ICT-ala

Table of Contents

List of Figures

List of Tables

1. Introduction

The impact of involuntary job displacement on individuals – as a result of firm-level reductions, such as plant closures or mass lay-offs – has been of great interest to labor economists already for decades. The pioneering studies on the cost of job displacement date back to 1980's (Kletzer, 1998). Since then, several methodologies and data sources have been utilized to further study the effects of job displacement. Especially the effect on earnings and employment outcomes has received a lot of attention (Addison & Portugal, 1989; Stevens, 1997). More recently, an emerging literature has also studied the effects on other outcomes, such as divorce probability, mortality and fertility decisions.

This thesis studies further the various effects of job displacement on displaced workers, both on their labor market outcomes and occupational choices using data from Finland. More specifically, the questions I seek to answer in this thesis are (i) how job loss has affected ICT employees' labor market outcomes and (ii) how these effects have varied over time and how they compare to other industries. The Finnish longitudinal employer-employee data (FLEED), containing information on all Finnish adult residents, enables a comprehensive analysis. Following the work of Huttunen and Kellokumpu (2016), I study the effects of plant closures and mass layoffs, which can be thought of as exogenous shocks to workers' careers, unrelated to performance of individual workers.

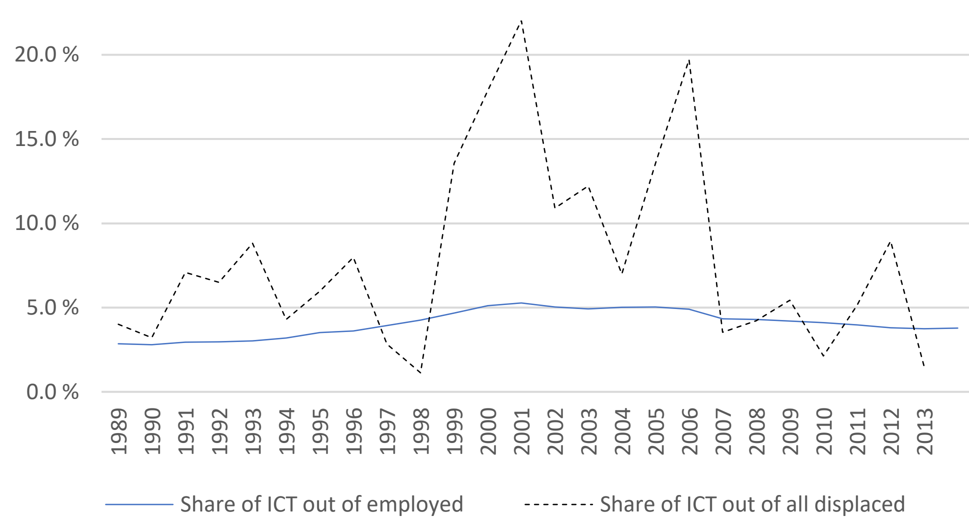
I follow the OECD recommendation for the definition of ICT sector[1]. ICT, acronym of Information and Communication Technology, consists of 12 subcategories, including production, reparation and other related services of computers, electronic components and communication devices as well as telecommunications, software design and manufacturing[2]. ICT is a relatively new and rapidly changing sector, meaning that the required skills may be very specific and outdate fast over time.

ICT sector has a special role in the Finnish economy. Its relative share in terms of employment is especially high compared to other developed countries. Finland reached the largest relative share of ICT specialists among all European countries in 2012 and is

[1] OECD definition from 2006 is the same as Statistics Finland is using. Although Statistics Finland's industry classification (TOL2008) does not include ICT as such, they provide explanation which of their categories belong to ICT. Definition available at: http://www.stat.fi/meta/kas/ict_sektori.html.
[2] See more detailed definition from *Appendix A*.

still holding the first place[3]. ICT has increased productivity through two main channels – by creating new products within the ICT sector and by increasing efficiency in the whole economy through investments in ICT (Pohjola, 2014). Within the ICT industry, the Finnish mobile phone giant Nokia has been very relevant. Its success resulted in a peak R&D expenditure of Finnish GDP, while computers and electronic equipment rose to top three category of the Finnish exports[4]. However, large dependence on ICT may also have downsides. The sector has experienced significant sector-specific shocks, which have led to several mass lay-offs within relatively short time period. These lay-offs include not only the downsizing of Nokia and Microsoft, but also many of their subcontractors, such as Perlos and Elcoteq, have terminated their business activities in Finland. *Figure 1* shows the evolution of the share of ICT workers in Finland, as well as the share of ICT among displaced. ICT sector's share of total employment was the highest in 2001 (5.3%), while the peak years in ICT's share of displacements were in 2001 (22.0%) and 2006 (19.7%). During most years, ICT has been overrepresented among total displacements.

Figure 1: Share of ICT sector of all employed and all displaced

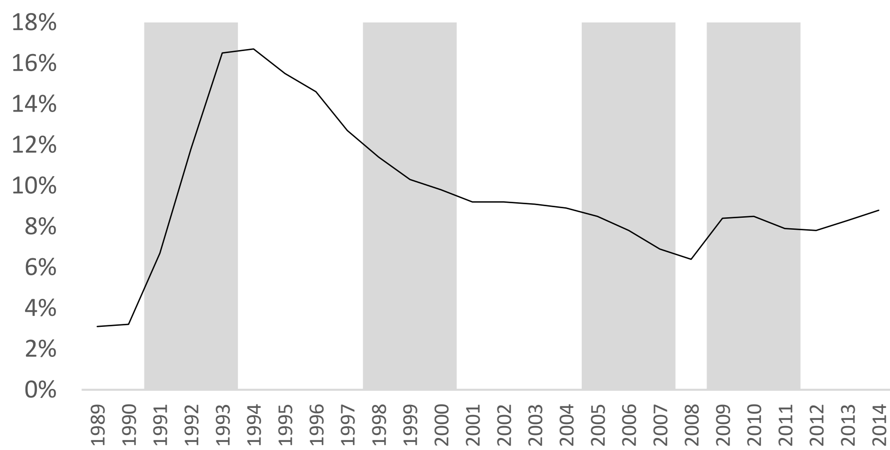


I study the effects of job loss on employment, income, probability of becoming an entrepreneur and probability of leaving the ICT sector. As in previous studies, I find that job loss leads to lower employment level and lower earnings (e.g. Huttunen &

[3] European Commission (2017): Statistics on employed ICT specialists by country.
[4] Bank of Finland (2016): Finnish economy: Success, challenges and outlook

Kellokumpu, 2016). However, the impact of job loss may vary depending on the economic cycle. When the economy is strong, displaced workers may receive more job offers compared to economic downturns. If this is the case, workers displaced during economic boom would suffer less in terms of employment outcomes and earnings. I study the impact of job loss on workers displaced during the following four periods: 1991-1993, 1998-2000, 2005-2007 and 2009-2011 (*Figure 2*). These four time periods differ in terms of macroeconomic conditions; for the workers displaced during 1991-1993 or during 2009-2011, an increasing unemployment rate was ahead, while for workers displaced during 1998-2000 or during 2005-2007 the trend was decreasing. Still, in terms of actual unemployment rate, 1991-1993 was significantly worse, while the other three periods faced rather similar conditions.

Figure 2: Unemployment rate in Finland during 1989-2014



I find that displaced ICT workers experience 5.2-14.4 percentage points lower employment level one year after job loss depending on the displacement period, while displaced non-ICT workers experience 3.3-23 percentage points lower employment level. The effect varies greatly over time periods, but there are no statistically significant differences between displaced ICT workers and other displaced workers, besides for workers displaced during 1991-1993. In terms of earned income, displaced ICT workers experience 3.2-15.0 percentages lower income one year after displacement, while displaced non-ICT workers experience 7.1-12.7 percentages lower income. In terms of effects on earned income, displaced ICT workers differ more from displaced non-ICT workers. My results suggest larger negative effects on earned income for displaced ICT workers after displacement in 2009-2011, 2005-2007 and 1998-2000. During the most recent time period, displaced ICT workers experienced 3.8 percentage points larger losses one year after displacement and 6.0 percentage points larger losses two years after displacement compared to other displaced workers. Nevertheless, the results for workers displaced during 1991-1993 are the opposite, suggesting 9.5 percentage points smaller losses for ICT workers one year after displacement, and 13.7 percentage points smaller losses two years after displacement.

All displaced workers have rather small increase of 0.1-0.7 percentage points in the probability of becoming an entrepreneur followed by displacement. Differences between displaced ICT workers and other displaced workers are not statistically significant. My fourth and last outcome variable, probability of staying in ICT sector after displacement, suggests that workers displaced during 2009-2011 have 9.8 percentage points lower probability to work in ICT sector one year after displacement and 11.6 percentage points lower probability two years after displacement, compared to non-displaced workers.

Although the effects of job displacements have been studied widely on aggregate level, sector and skill specific differences have received less attention. This thesis contributes to the literature by giving insight on the effects of job loss specifically on ICT sector as well as on effects during the more recent years. The thesis proceeds in the following way. Section two introduces the theoretical background and previous literature, section three presents the methodology, section four provides descriptive analysis and section five summarizes the results. Finally, section six concludes.

2. Literature Review

In dynamic economies, jobs are created and eliminated. Effects of job displacement can be broadly divided into private and public effects, private referring to individuals and firms while public refers to the society. This thesis is solely considering the effects of job loss on individuals. The first part of the literature review covers related theories of job search and human capital, whereas the second part gives an overview of the previous empirical evidence on the effects of job loss.

2.1. *Theoretical background*

Before moving to a more detailed description of mechanisms causing the heterogeneity in labor market outcomes, I start this section with a simple framework of job search theory. Then, I discuss the relevant parts of human capital theory to understand how human capital acts as a key factor in creating heterogeneity to the costs of job loss.

Job displacement includes loss of an established job and the need to seek for reemployment. Job displacement creates an interruption to a worker's career. This interruption forces workers to make decisions on whether to search for a new job or leave the labor market. Simple theory of job search helps to understand the decision process the displaced person first needs to go through. Reservation wage, indicating the wage level at which an individual is indifferent between working and not working, plays an important role determining both whether a person decides to become a job seeker or a nonparticipant, and whether a job seeker accepts a job offer (Cahuc, Carcillo, & Zylberberg, 2014). Reservation wage x is affected by labor market characteristics $\Omega = \Omega(H, z, q, \lambda, r)$, where H is the (known) distribution of possible wages in the labor market, z is the net income associated with job search, q is the rate at which any job can disappear ("rate of job destruction"), λ arrival rate of job offers and r is the interest rate. First, reservation wage $x(\Omega)$ determines whether a person enters the labor market:

$$\begin{cases} x(\Omega) \geq R_I & \rightarrow participant \\ x(\Omega) \leq R_I & \rightarrow nonparticipant \end{cases}$$

If the alternative income R_I, that a nonparticipant receives each day, is lower than the expected utility as a job seeker, i.e. the reservation wage, the person becomes a participant. Job search is closely linked to the available job opportunities. Job seeker does not know what her maximum potential salary is, which means that more search gives her more information. Displaced workers are expected to receive job offers based on their previous salary and investments in human capital.

The decision of accepting or rejecting job offers is defined as:

$$\begin{cases} w > x(\Omega) & \rightarrow employed \\ x(\Omega) \geq w > R_I & \rightarrow unemployed \end{cases}$$

A job seeker accepts the offered wage w, if it is larger than her reservation wage. Similarly, job seeker rejects the offer and stays as unemployed if her reservation wage is higher than offered wage rate w. Offered wage still needs to be higher than alternative income R_I, for the person to stay in the labor market. In the basic model of job search, average duration of unemployment, T_u, is an increasing function of reservation wage x:

$$T_u = \frac{1}{\lambda[1 - H(x)]}$$

Where the arrival rate of job offers (λ) and the probability of receiving job offer with a wage larger than reservation wage $1 - H(x)$, together describe the exit rate from unemployment $\lambda[1 - H(x)]$. In terms of my focus group, ICT sector employees, a higher than average reservation wage is possible (thereby potentially prolonging the unemployment spell), while the arrival rate of job offers can be higher than average (if these workers are highly skilled) or lower than average (if the worker's skills are very specific).

To further understand the heterogeneity of responses to job loss, I review the theory of human capital. Worker characteristics, especially education, may have a large impact in the overall displacement effects. Becker (1964) introduces human capital depreciation rate, which refers to decreasing value of human capital over time. Employer can contribute either to accumulating or depreciating her workers human capital by deciding whether to provide on-the-job training. Training is divided into specific and general training, the former increases worker's productivity in one type of work, while the latter increases worker's productivity in all types of work. If all human capital was general, the costs of job loss would be minor (Topel, 1990).

Human capital theory suggests that in case of unemployment, individual's human capital depreciates unless she invests in training or education. Workers from different skill levels may be affected differently by career interruption if their human capital appreciation and depreciation rates differ (Huttunen & Kellokumpu, 2016). To some extent, earnings losses also reflect loss of job-specific or firm-specific capital and job tenure (Stevens, 1997). The level and speed of wage recovery depends on workers ability to reinvest in human capital. There may be also barriers to reinvest in certain type of specific capital.

Heterogeneity of effects is also partly explained by varying job search costs (depending on time and job market) and the extent of geographical mobility (Cahuc, Carcillo, & Zylberberg, 2014). Geographically mobile labor force is an important determinant for well-functioning and effective labor markets. More mobile labor force reorganizes and reaches the social optimum faster. Higher education level may increase geographical mobility due to enhanced communicative capacity and adaptability.

To conclude, reservation wage determines whether the displaced person decides to search for and accept a new job, while job seeker's human capital is expected to depreciate during unemployment. In terms of my focus sample, displaced ICT workers, it is not evident what sort of differences to expect based on the theory. If their skills were merely job- or firm-specific, their losses would be larger. On the other hand, a lot also depends on their ability to reaccumulate human capital.

2.2. Empirical literature

Job displacement has been associated with several persistent negative effects in the previous literature: large and long-lasting earnings losses, increased job instability and larger probability of unemployment. The effects of job displacement have been explored both on worker's economic and non-economic outcomes.

Job loss reduces workers earnings significantly, according to survey information (Kletzer, 1998; Stevens, 1997) and administrative data (Eliason & Storrie, 2006; Huttunen & Kellokumpu, 2016). Longer duration of unemployment leads to larger subsequent earnings losses (Addison & Portugal, 1989). The effects are strongest immediately followed by displacement, but they are very persistent and long-lasting. Job displacement not only decreases earnings but it also increases probability of temporary employment relationships and probability of further job losses (Stevens, 1997). In fact, large part of the lifetime earnings losses of displaced can be explained by subsequent job losses. In addition to that, job loss decreases home ownership rates, which suggests that life-time choice sets are affected if home ownership decisions are made based on long-term earnings rather than short-term (Handwerker & von Wachter, 2010). Alongside with the negative economic outcomes, job displacement also effects worker's life in several other dimensions. Displaced workers experience higher health risks, higher mortality rates (Sullivan & von Wachter, 2009) and lower fertility rates (Huttunen & Kellokumpu, 2016).

In general, higher education level is positively correlated with greater labor market participation, better labor market performance and lower average unemployment rate (Cahuc et al., 2014). In terms of heterogeneity of responses, Adda et al. (2017) show that human capital depreciation rates are faster and vary more over career cycle in abstract occupations, where usually higher education levels are required. On the other hand, higher level of education may also give a better basis to reaccumulate human capital. Von Wachter and Handwerker (2010) find that cost of job loss is hump-shaped to education – largest and most long-lasting losses are experienced among workers with some college or high school degree, while workers without high school degree and workers with four or more years of college suffer less.

Topel (1990) reports that in one of his data sources earnings losses are strongly related to prior job tenure, although the correlation is not visible in another data set. He argues that specific human capital is a large determinant of the size and versatility of the costs of job displacement. The losses are greater among workers with more seniority, both in terms of age and experience. He also suggests that specific capital increases the stability of employment relationships, indicating that on average, displaced workers maintain less specific capital than non-displaced.

3. Methodology

3.1. Data

The data source of this thesis is Finnish longitudinal employer-employee data (FLEED). The data set consists of all Finnish residents aged 15-70 and covers yearly information from 1988 until 2014. This translates to around four million observations per year during the 27 sample years. This thesis covers job displacements that have happened during 1991-2011. I am focusing on four different time periods: 1991-1993, 1998-2000, 2005-2007 and 2009-2011. The biggest advantages of this data set are its large sample size and detailed information on worker characteristics, both from preceding and following periods of job displacement.

In my analysis, I consider individuals who were “displaced”, i.e. workers who lost their job due to a plant closure or mass lay-off. Job loss followed by the aforementioned reasons can be considered as an exogenous interruption to a worker's career that is unlikely to be related to individual's own characteristics or work performance (Huttunen & Kellokumpu, 2016). Other causes of job loss are excluded. A job displacement needs to be permanent, not temporary. A worker is considered as "displaced" even if she finds another job immediately followed by displacement.

A plant closure has happened during year t, if a plant that employed workers at the end of year $t-1$, does not exist in the data at the end of year t or any other following year. If after a plant closure, at the end of year t, more than 70% of the former employees work in the same new plant, it is not considered as real closure and therefore its workers are not considered as "displaced". This arrangement excludes "false closures" which are in reality mergers or acquisitions.

Mass lay-off has happened during year t, if the plant employs more than 30% less employees at the end of year t compared to the number of workers it employed at the end of year $t-1$. A person is considered as "displaced" due to a mass lay-off if a person worked for the company at the end of year $t-1$, but was not anymore working for that specific company at the end of year t. A mass lay-off is considered as "false" if more than 30% of the laid off people work in a same single plant at the end of year t. Mass lay-off is also considered as false if by the end of year $t+1$, the plant expands by more than 30%.

Since in a case of mass lay-off the plant is able to decide which individuals it will dismiss, there is a chance of negative selection. In order to mitigate this problem, I include all individuals who worked in a plant that experienced a mass lay-off, as "displaced". This means that the sample includes also persons who were in fact not displaced, but their plant was affected. However, it seems to be rather common that one or two years after a large mass lay-off, the plant closes permanently. Therefore, often the largest negative effects of job loss are observed during $t+2$, instead of $t+1$.

Following the previous literature (e.g. Huttunen & Kellokumpu, 2016), I only consider plants with at least 50 employees and maximum of 2500 employees prior to the closure or mass lay-off. Plant size minimum is restricted to exclude potential company failures that are directly due to employee characteristics. My data sample consists of persons, who at time t were 18-61 years old. The upper age limit is set to exclude people who are exiting labor force due to retirement. However, the upper limit might still be too high and distort the results for years following the displacement, especially for years after $t + 2$ when older persons of the sample start to reach retirement age. To ensure that the employment relationship prior to job displacement was “stable”, it is common to restrict the analysis to employees who have been employed for certain period prior to the job loss, usually six to sixteen quarters (Handwerker & von Wachter, 2010). My analysis is considering employees who have been employed at time t, $t - 1$ and $t - 2$. This implies, that they have been employed for at least 7 quarters prior their job loss, even more if the plant closure happens later than during the first quarter of t.

My control variables are the following: age, gender, native language, region, education level, education field, plant size, marital status, number of below three-year-old children and employer type defined as either private or public sector. In addition to these variables I also use the variables for individual identification number, employer’s identification number, employer’s industry and individual’s employment status. Native language is a dummy variable called “foreign language”, which takes value zero if individual’s mother tongue is Finnish or Swedish. Region is divided into five areas based on individual’s place of residence: capital region (Helsinki, Espoo, Vantaa and Kauniainen), Turku area, Tampere area, Oulu area and other. Education level takes values from zero to eight, zero referring to no education or unknown education and eight referring to doctoral level education. Education field is defined based on educational classification of Statistics Finland, which divides education into nine fields[5]. Plant sizes are calculated as number of people who have that plant as their employer in FLEED. A company is considered to operate in a private sector if its ownership type is informed as “private domestic” or “foreign owned”.

Employee’s industry is determined in the data set based on her employer’s industry. This means, that some employees are falsely categorized as ICT employees and some are falsely categorized as non-ICT employees. False ICT category should not be that common, since mainly support function employees working in an ICT company are belonging to this group. However, falsely categorizing as non-ICT might be a larger

[5] Educational classifications available at: http://tilastokeskus.fi/meta/luokitukset/koulutus/001-2010/1.html.

issue, since single ICT specialists working in a non-ICT company are not included. Sector is not known for those who are unemployed or outside of the labor force.

3.2. Econometric Approach

In order to measure the effects of job displacement on individuals, I follow the common differences-in-differences econometric approach used in the previous literature (Huttunen 2016; Stevens, 1997), although with small modifications. The effects of involuntary job loss on the labor market outcomes and occupational choices of worker i at time t, are estimated using the following equation:

$$\Delta Y_{it+j} = X_{it}\beta + D_{it}\delta + ICT_{it}\zeta + D_{it} * ICT_{it}\varphi + \gamma_t + u_{it}$$

where dependent variable Y_{it} indicates the estimated changes in individual i's outcome variables between years t and $t+j$, where $j = -3, -2, -1,\ 0,\ 1,\ 2 \dots 8$. As outcome variables, I consider employment level, annual earnings, self-employment and probability of staying in the ICT sector[6]. Outcome variable *earnings* has two categories: earned income and all income. Earned income is more straight forward and less problematic to form, but all income describes perhaps better the actual losses the individual is subject to, as the actual income does not drop to zero for unemployed due to social benefits[7]. Both income measures are adjusted with consumer price index.

Let us now look at the right-hand side variables of the model. X_{it} is a vector of company's and individual's observable characteristics that influence worker i's ability and

---

[6] Employment status is formed with the "main activity"-variable *(pääasiallinen toiminta)*. A person is employed if she is not unemployed or outside of the labor force. Self-employment is determined with "professional status"-variable *(ammattiasema)*.

[7] *Earned income* is the sum of employment income *(työtulo)* and entrepreneurial income *(yrittäjätulo)*. *All income* is formed as the sum of taxable capital income in state taxation and taxable non-capital income in state taxation. Since state taxation does not apply to those earning less than 16,900 euros per year (situation in 2017), this measure is rather problematic. For persons who do not have taxable non-capital income, but do have information on employment income, I replace the all income with the information on employment income. Since entrepreneurial income can be taxable as capital or non-capital income, I only add that income to individuals who are missing information on both taxable non-capital income and taxable capital income. I have only limited information on social benefits that are non-taxable. These benefits would include for example child benefit, housing benefit and social assistance. I have information only on general housing benefit which I have added to taxable income in order to form *all income*. In the total data set of 101,4M observations, 2,8M observations still have missing information of *all income* after these modifications. 61.54% of these people are students and 29.73% quantified as "other, outside of the labor force). In addition to that, 55.88% percent of these people are below 18 years old. This means, that most of them are not going to be included in my data sample, and thus this missing information should not be a cause for concern.

labor market outcomes; D_{it} is a dummy variable indicating the incidence of job displacement during year t; ICT_{it} is a dummy variable indicating whether the person worked for ICT sector at the end of year t; $D_{it} * ICT_{it}$ is an interaction term that takes a value if the person was displaced from the ICT sector during year t; γ_t is a vector of dummy variables indicating the year in question. Variables of γ_t control for year-specific, economywide changes in outcome variables caused by economic fluctuations and other trends.

The treatment group consists of employees who have been displaced due to a plant closure at time t. Control group consists of workers, that were employed but not displaced at time t, but otherwise meet the sample requirements at time t, i.e. are 18-61 years old, work in a plant sized 50 – 2,500 employees and were employed also at the end of years $t-1$ and $t-2$.

3.3. Limitations

There are several potential threats to the validity of the analysis. Although plant closures and mass lay-offs are considered as exogenous interruptions to worker's careers, it is possible that they can be anticipated. If the shock is anticipated, the most skilled workers might leave the company by the time of mass lay-off or plant closure. Another problem with the definition of displacement arises if wage changes in a firm prior to closure encourage skilled workers to leave the company earlier and only the workers who wait until the very end, become "displaced" (Kletzer, 1998). In both cases, the final sample of "displaced" would be negatively selected and therefore most likely overstate the cost of job loss. On the other hand, number of displaced workers would be understated.

Since my data set consists of yearly observations, it is possible that the most skilled workers affected by the shock have already found new employment by the end of the year, when their employment status is reviewed. This is especially a relevant concern, if plant closure has happened in the beginning of the year, and displaced employees have already had several months to seek for new opportunities.

Although the underlying assumption in this thesis is that plant closures and mass lay-offs are not related to individual performance, it cannot be completely excluded. Especially in smaller firms, individual's performance can be very much linked to company's success, but restricting the company size to minimum of 50 employees should mitigate this concern.

4. Descriptive analysis

In order to compare the outcomes of displaced and non-displaced, one needs to understand how those two groups differ. This section presents the differences based on observable characteristics. As explained in the previous section, my control variables are age, gender, language, region, education level, education field, plant size, marital status and employer type defined as private or public sector. From 2006 onwards, I also consider the number of below three-year-old children as a control. I present differences in pre-displacement characteristics in three different dimensions: (1) differences between all displaced and non-displaced workers in the sample, (2) differences between displaced ICT and non-displaced ICT workers, and (3) differences between displaced ICT workers and displaced non-ICT workers.

For my identification strategy to be valid, I am assuming parallel trends in outcome variables between displaced and non-displaced employees had the displacement not happened. This assumption does not require employees to have the same observable characteristics, but sufficient similarity would make the assumption more plausible. *Table 1* presents the differences between all displaced and non-displaced workers in the total sample period based on observable pre-displacement characteristics[8].

Displaced workers are on average one year younger than non-displaced and around two percentage points more likely to be females. They are slightly more likely to work in ICT sector, they earn less and work in smaller plants. Displaced workers have lower education level, they are less likely to be married, less likely to work in private sector and slightly more likely to speak a foreign language as their mother tongue. All differences in observable characteristics are statistically significant.

[8] I present here only the average differences during the total time period, since the yearly differences are not radically different. Descriptive statistics separately for the four time periods are presented in *Appendix B*.

Table 1: Descriptive statistics of displaced and non-displaced workers

	Displaced	*Non-displaced*	*Difference*
Age	39.39	40.42	*-1.027****
Male	0.49	0.51	*-0.022****
ICT sector	0.07	0.07	*0.007****
Earned income	30342	34629	*-4287****
All income	32794	36991	*-4197****
Plant size	321	474	*-153****
Education level	3.27	3.54	*-0.273****
Married	0.50	0.55	*-0.046****
Private sector	0.54	0.57	*-0.031****
Foreign language	0.03	0.02	*0.006****
Observations	*1,008,116*	*21,037,907*	

Observations include all workers from the sample during all observation years. Pre-displacement characteristics are collected from the year prior to the job loss. Stars indicate significance of differences in observable characteristics, at 10% (*), 5% (**) and 1% (***) level.

As I am interested in the effects of job loss specifically on ICT sector employees, I also compare the observable characteristics between displaced ICT and non-displaced ICT workers. *Table 2* presents the difference.

Table 2: Descriptive statistics of displaced ICT and non-displaced ICT workers

	ICT Displaced	*ICT non-displaced*	*Difference*
Age	37.93	37.88	*0.050*
Male	0.64	0.65	*-0.010****
Earned income	45824	47819	*-1995****
All income	48636	51029	*-2393****
Plant size	309	515	*-206****
Education level	4.01	4.31	*-0.298****
Married	0.52	0.54	*-0.019****
Private sector	0.82	0.92	*-0.092****
Foreign language	0.03	0.03	*-0.005****
Observations	*72,643*	*1,376,783*	

Observations include all displaced workers from the sample during all observation years. Pre-displacement characteristics are collected from the year prior to the job loss. Stars indicate significance of differences in observable characteristics, at 10% (*), 5% (**) and 1% (***) level.

Similarly to all displaced workers, also displaced ICT workers are slightly more likely to be females, earn less, work in smaller plants and are less educated. The income differences are smaller in ICT sector, but differences in education level are larger. Also displaced ICT workers are less likely to be married and less likely to work in private sector. However, there are a couple of interesting differences between displaced ICT workers versus non-displaced ICT workers, compared to differences between displaced and non-displaced. Unlike in the total sample, displaced ICT sector workers are likely to be older than non-displaced ICT workers. Among total sample, displaced employees are likely to be younger, with significant difference during all time periods, although the magnitude varies. Also, the displaced ICT workers are less likely to be foreign language speakers than non-displaced ICT workers, while in total sample, displaced are more likely to speak foreign language as their mother tongue.

Another noteworthy difference in characteristics of ICT workers compared to non-ICT workers, is the difference between differences in all income and differences in earned income. In total sample, during all displacement periods except 2005-2007, the difference in earned income is larger than the difference in all income. However, when I compare the differences in income type differences of displaced and non-displaced ICT workers, the situation is the opposite. For them, during all displacement periods except 1998-2000, the difference in all income is larger than the difference in earned income. This means, that if the levels of social benefits prior to the displacement are the same between displaced and non-displaced, capital incomes of non-displaced ICT workers are higher than capital incomes of displaced ICT workers.

As my analysis explicitly focuses on the possibly varying effect of job loss on ICT and non-ICT workers, *Table 3* presents the differences in pre-displacement characteristics between displaced ICT workers and displaced non-ICT workers.

Table 3: Descriptive statistics of displaced ICT workers and displaced non-ICT workers

	ICT Displaced	*Non-ICT Displaced*	*Difference*
Age	37.93	39.50	*-1.568****
Male	0.64	0.48	*0.158****
Earned income	45823.61	29141.13	*16682****
All income	48636.10	31564.49	*17072****
Plant size	309.48	321.44	*12****
Education level	4.01	3.21	*0.803****
Married	0.52	0.50	*0.027****
Private sector	0.82	0.53	0.292***
Foreign language	0.03	0.03	*-0.000*
Observations	*72,643*	*935,473*	

Observations include all displaced workers from the sample during all observation years. Pre-displacement characteristics are collected from the year prior to the job loss. Stars indicate significance of differences in observable characteristics, at 10% (*), 5% (**) and 1% (***) level.

Displaced ICT workers are on average 1.5 years younger than non-ICT displaced workers. They are 16 percentage points more likely to be males, three percentage points more likely to be married and 30 percentage points more likely to work in private sector. ICT workers earn 57% more than non-ICT workers, they work in slightly smaller plants and have 0.8 points higher education status. In terms of foreign language speakers, there are no significant differences.

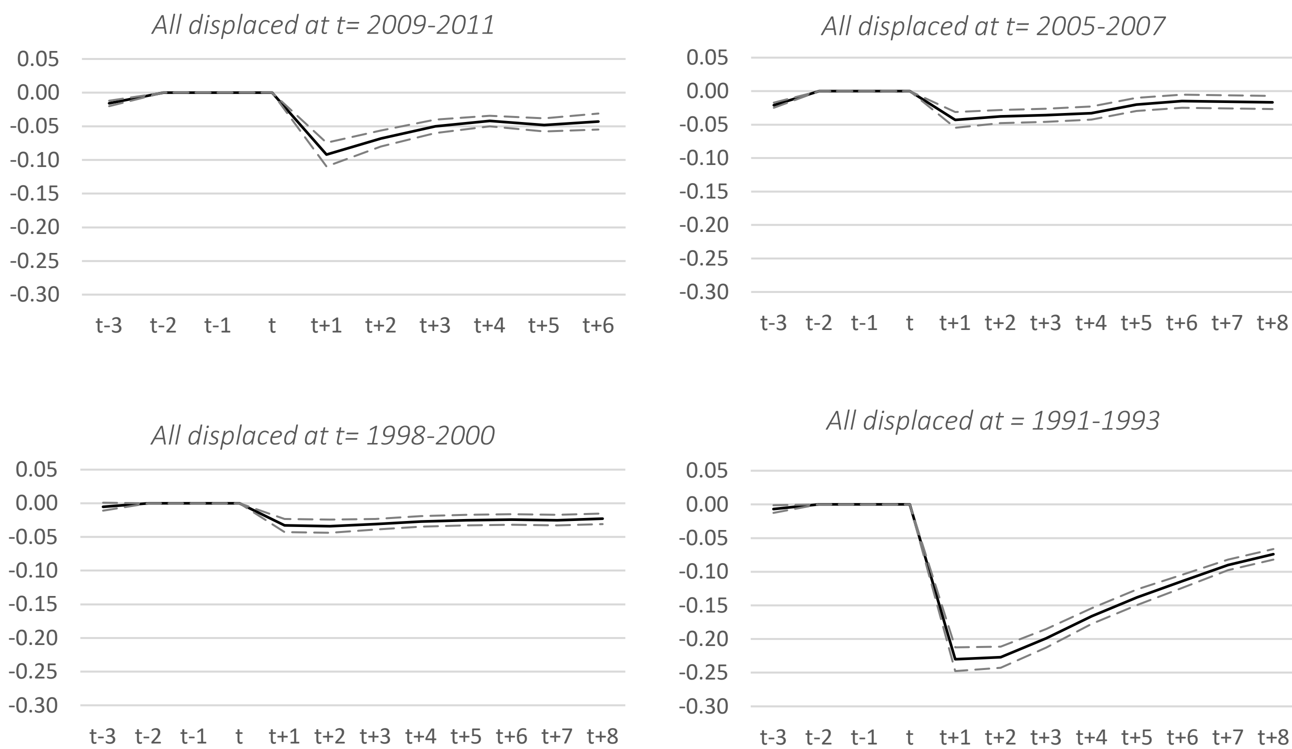
5. Results

This section presents the effects of job loss on employment, earnings, probability of becoming self-employed and probability of staying in the ICT sector. Within each section, I first present the analysis for workers in all sectors and then focus on the ICT sector. My results include four time periods, but the focus is on the most recent displacements that happened during 2009-2011.

5.1. Effect on employment

Figure 3 presents the differences in employment level between displaced and non-displaced workers. The estimated effect is the largest at year $t+1$, when displaced workers have just lost their jobs. This effect varies from 23.0 percentage points lower employment level after a job loss during the worst recession years (1991-1993) to 3.3 percentage points loss in employment level after job loss during 1998-2000. Workers displaced during economic downturns experience larger losses compared to workers displaced during economic booms. However, job loss during the recession period of 1991-1993 leads to significantly larger losses in employment level compared to any other observation period. Workers displaced during the most recent period (2009-2011) experienced 9.2 percentage points lower employment level at $t + 1$ and 6.8 percentage points lower employment level at year $t + 2$.

Figure 3: Effect of job loss on employment in Finland

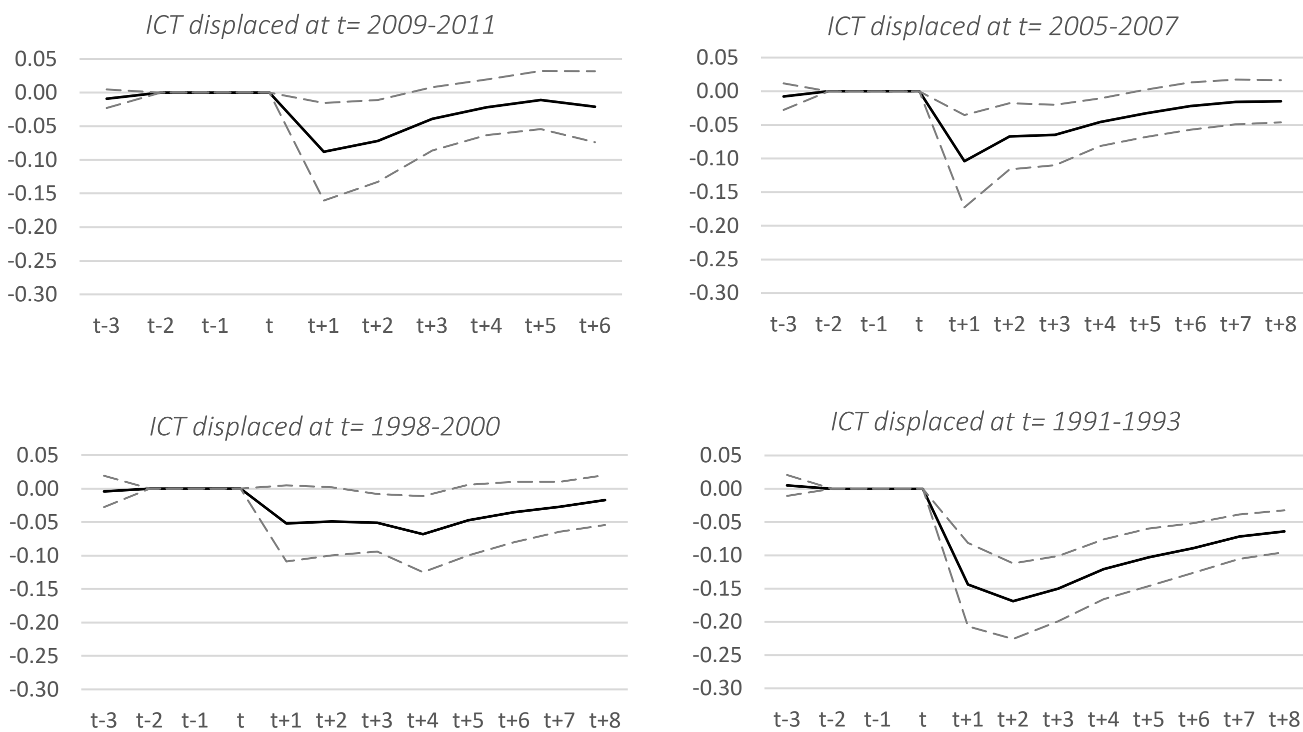


Figures represent the difference in employment level between displaced and non-displaced workers. The values in y-axis represent percentage point differences caused by job loss. Time t refers to displacement year. Employment level is conditioned to be same (i.e. employed) among displaced and non-displaced during t, $t - 1$ and $t - 2$. Dashed grey lines represent 95% confidence intervals.

Negative effect of job loss on employment deteriorates gradually, but is still statistically significant across all observation years, i.e. even after six to eight years after job loss. In order to avoid negative selection, past employment level differences are controlled until $t - 2$. Still, there is negative and significant difference of 0.5-2.0 percentage points in employment level during year $t-3$. Lower pre-displacement employment levels indicate of negative selection of displaced workers.

Since my focus is on ICT employees, I next compare the effect of job loss on employment of ICT workers that were displaced during the same time periods. *Figure 4* presents the differences in employment levels between displaced ICT workers and non-displaced ICT workers. Similarly to all displaced workers, also ICT workers experience by large the most significant losses if they are displaced during 1991-1993. Rest of the time periods are much more similar to each other.

Figure 4: Effect of job loss on employment level in ICT sector



Figures represent the difference in employment level between displaced and non-displaced workers. The values in y-axis represent percentage point differences caused by job loss. Time t refers to displacement year. Employment level is conditioned to be same (i.e. employed) among displaced and non-displaced during t, $t-1$ and $t-2$. Dashed grey lines represent 95% confidence intervals.

ICT employee's job loss during 2009-2011 leads to 8.8 percentage points lower employment level at $t+1$ and 7.2 percentage points lower employment level at $t+2$. This means that compared to displaced non-ICT workers, ICT workers suffer less at $t+1$, but more at $t+2$ compared to their counterparts. Also, displaced ICT workers are not as negatively selected as other displaced workers. However, these results are not statistically significant.

For most time periods, there are no statistically significant differences in displacement effect between displaced ICT and displaced non-ICT employees. *Table 4* presents the results of the interaction term *displaced*ICT*, which estimates the difference.

Table 4: Difference in employment effects between ICT and non-ICT workers

	t-3	*t+1*	*t+2*	*t+3*	*t+4*	*t+5*	*t+6*
*09-11 displaced*ICT*	0.007	0.004	-0.004	0.011	0.02	0.037**	0.022
	(0.005)	(0.028)	(0.025)	(0.019)	(0.017)	(0.017)	(0.021)
N	*2,275,351*	*2,277,089*	*2,271,197*	*2,265,540*	*2,259,827*	*1,494,342*	*757,131*
*05-07 displaced*ICT*	0.013	-0.061**	-0.029	-0.029	-0.013	-0.013	-0.007
	(0.008)	(0.029)	(0.020)	(0.018)	(0.013)	(0.013)	(0.013)
N	*1,972,490*	*1,971,227*	*1,966,085*	*1,961,311*	*1,956,666*	*1,951,656*	*1,946,294*
*98-00 displaced*ICT*	0.001	-0.019	-0.015	-0.020	-0.041	-0.022	-0.011
	(0.009)	(0.024)	(0.021)	(0.018)	(0.025)	(0.023)	(0.019)
N	*1,948,690*	*1,945,211*	*1,939,846*	*1,934,894*	*1,930,107*	*1,925,318*	*1,920,139*
*91-93 displaced*ICT*	0.012**	0.086***	0.058***	0.049***	0.045***	0.035**	0.025*
	(0.005)	(0.023)	(0.021)	(0.018)	(0.017)	(0.016)	(0.014)
N	*1,342,765*	*2,083,687*	*2,078,551*	*2,072,903*	*2,066,989*	*2,060,690*	*2,053,993*

*Table 3 reports the coefficients of interaction term displaced*ICT. Values for t, $t-1$ and $t-2$ are conditioned to be same (i.e. employed), and thus the coefficient for is zero for those three columns. Number of observations at time t, $t-1$ and $t-2$ are the following: 2,282,912 (2009-2011); 1,976,699 (2005-2007); 1,950,455 (1998-2000) and 2,083,687 (1991-1993). For observation period 2009-2011, number of observations drops dramatically after $t+4$, since the data set provides information of 2010 displaced only until $t+5$, and of 2011 displaced until $t+4$. Similarly, number of observations also drops for observation period 1991-1993 at $t-3$, since that data is not available for persons displaced during 1991. Standard errors are in parentheses. Stars indicate significance, at 10% (*), 5% (**) and 1% (***) level.*

The only time period with significant differences for years $t+1$ and $t+2$ is 1991-1993, suggesting 8.6 percentage points higher employment level during $t+1$ and 5.8 percentage points higher employment level during $t+2$ for displaced ICT workers compared to displaced non-ICT workers. The difference is significant until $t+5$, but diminishes gradually. Also displacement period 2005-2007 reports statistically significant difference for $t+1$, suggesting 6.1 percentage points lower employment level for displaced ICT workers compared to displaced non-ICT workers. For displacement period 1998-2000 the difference is negative but insignificant, while for 2009-2011 it is especially close to zero, suggesting no difference in effects of job loss on employment between displaced ICT employees and other displaced. Overall, it seems that the displacement effects on employment are not categorically different for ICT employees.

Positive interaction term during $t-3$ of all displacement periods denotes that prior to the displacement, average employment levels of displaced ICT workers are closer to the levels of ICT employees that are not displaced, compared to the employment level differences between displaced and non-displaced non-ICT workers. Therefore, it seems that in general, displaced ICT employees are less negatively selected compared to displaced employees from other sectors. Still, pre-displacement regression estimates of models including control variables predict statistically significant difference between displaced ICT workers and displaced non-ICT workers only for employees displaced during 1991-1993. However, regressions without control variables suggest larger differences, with statistically significant and positive pre-displacement estimates for all displacement periods except 1998-2000.

5.2. *Effect on earnings*

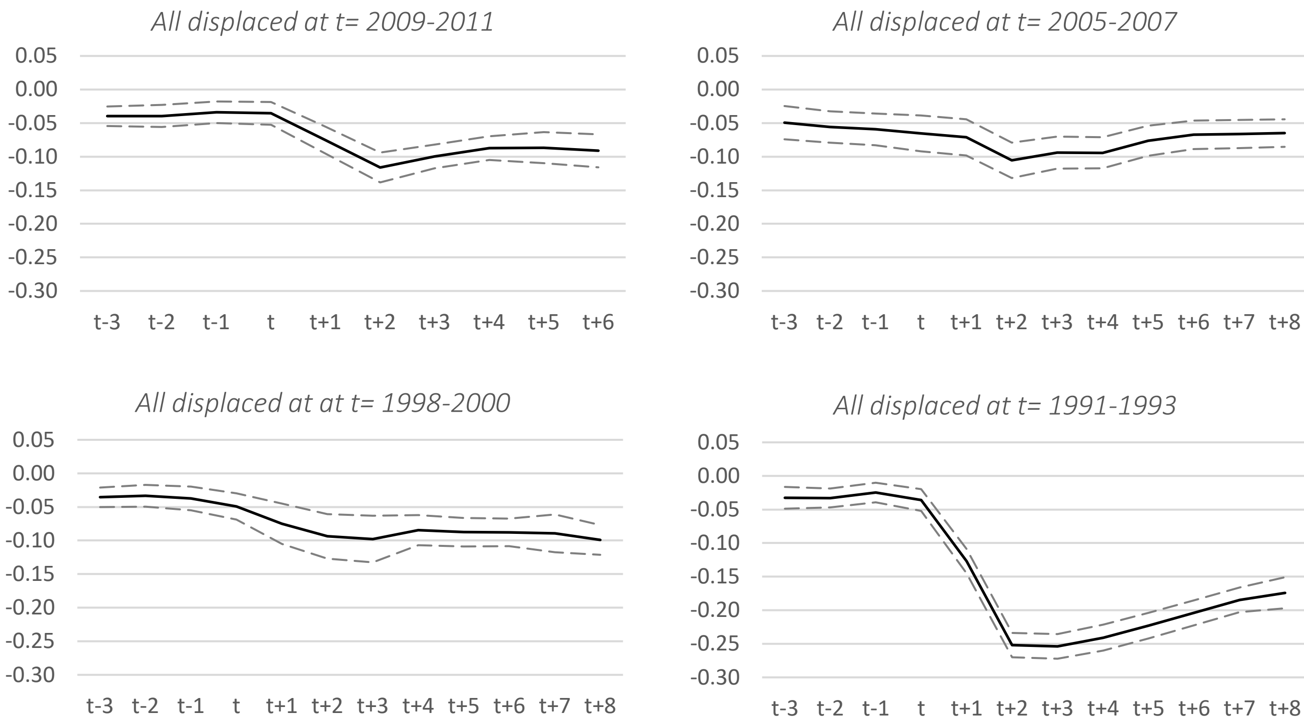
My main interest regarding the effects on earnings is on *earned income*, defined as the sum of employment income and entrepreneurial income. In order to measure the effects on earned income I use two outcome variables: earned income measured as monetary annual earnings, and secondly, logarithmic form of annual earned income[9]. However, due to the substantially large number of individuals with zero incomes during the years followed by job loss, logarithmic results considerably overestimate the true effects of

[9] Logarithmic earnings are calculated as ln(earnings+1).

displacement. Missing observations in earned income create the most prevailing challenge for 1991-1993 period, when around 20% of displaced and 14% of non-displaced have zero earned income during the follow-up period. However, this is a noteworthy problem also during other time periods, for example in 2005-2007, 12% of displaced and 11% of non-displaced individuals have zero earnings by year $t + 6$. Logarithmic results of regressions including control variables suggest losses of 28-118% for $t + 2$, while results of regressions without control variables suggest losses of 52-122% for $t + 2$. Due to these challenges, I focus on the monetary losses in earned income. To simplify interpretations, I convert the differences into percentages by dividing the monetary results by the pre-displacement mean values of earned income of displaced non-ICT employees and displaced ICT employees.

Figure 5 presents the differences in earned income between all displaced and non-displaced workers. Displaced workers have lower earned income compared to non-displaced workers, both prior to the job loss as well as after the job loss. This implies, that displaced workers are negatively selected not only in terms of employment, but also in terms of earnings. In case of all time periods, the differences between displaced and non-displaced workers are statistically significant for all pre-displacement years as well as for all post-displacement years.

Figure 5: Effect of job loss on earned income in Finland

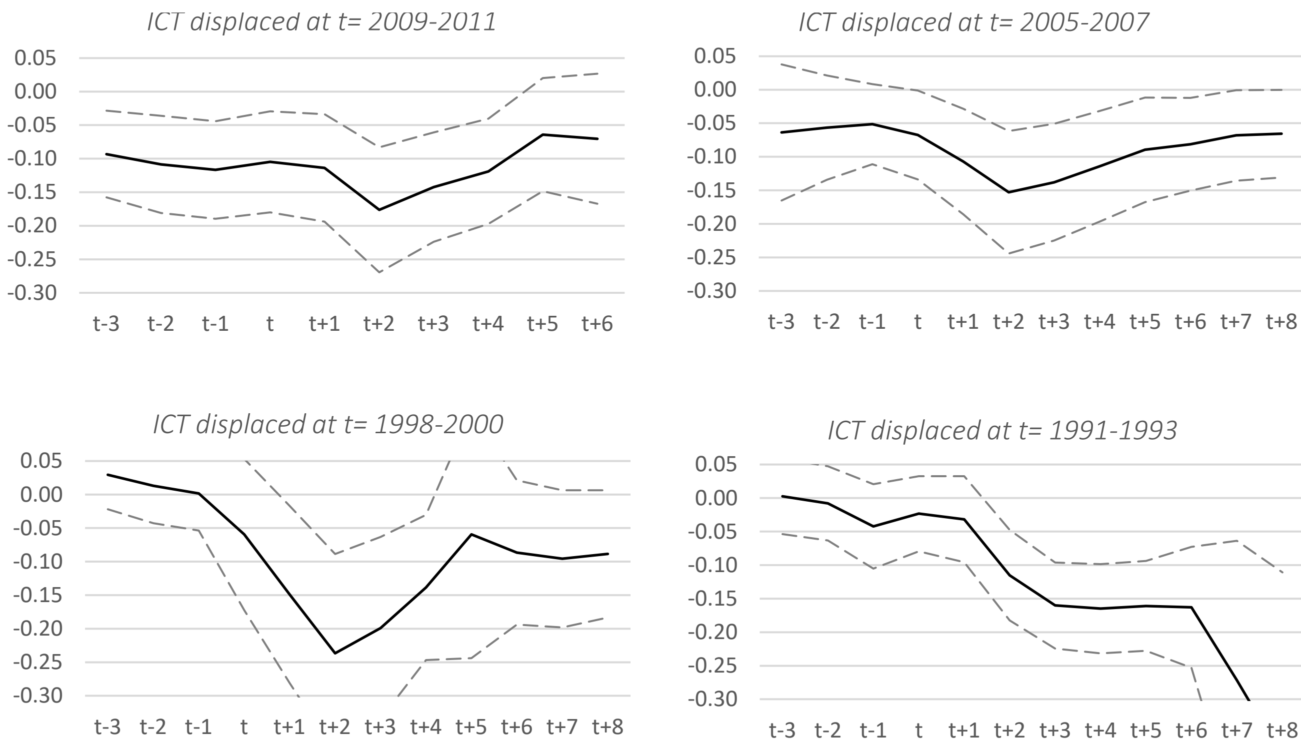


Figures present the estimated difference in earned income between displaced and non-displaced workers. The values in y-axis represent the differences in percentages. Time t refers to displacement year. Dashed grey lines represent 95% confidence intervals.

Job loss in 2009-2011 leads to 7.5% lower earnings at $t+1$ and 11.6% lower earnings at $t+2$. Prior to job loss, during $t-1$, displaced workers had 3.4% lower earnings, indicating of 8.2 percentage points loss from $t-1$ to $t+2$. Similarly to the effect of job loss on employment, also the effect on earnings is most severe after job loss during 1991-1993, while the other periods are more alike.

Next, I compare the effect on earned income of all displaced workers with effect on displaced ICT workers. For ICT workers displaced during 2009-2011, the results suggest 17.6% lower earned income two years after job loss, but also around 10% lower earned income prior to the job loss. In case of this time period, displaced ICT employees' earnings recover rather fast, reaching a higher income level five years after job loss, than they had prior to the displacement. ICT workers displaced during other periods experience 11.5-23.7% lower income at $t+2$ compared to their non-displaced counterparts, and do not achieve their previous income level during the observation period.

Figure 6: Effects of job loss on earned income of displaced ICT workers



Figures present the estimated difference in earned income between displaced and non-displaced workers. The values in y-axis represent the differences in percentages. Time t refers to displacement year. Dashed grey lines represent 95% confidence intervals.

Unlike in terms of employment, here we can see differences in effects on displaced ICT workers compared to displaced non-ICT workers. The evidence is mixed, but statistically significant across all periods at $t+1$ and at $t+2$. ICT workers displaced during the recession period of 1991-1993 suffered less in terms of income (-11.5% at $t+2$) than displaced non-ICT workers (-25.2% at $t+2$). However, during all other time periods, ICT workers suffered more than displaced non-ICT workers. For employees displaced during 2009-2011, the difference is significant at 5% level, suggesting 6.0 and 4.3 percentage points larger income losses for ICT workers compared to non-ICT workers at year $t+2$ and $t+3$, respectively.

In order to take into account the pre-displacement differences, I next compare experienced losses in income between pre-displacement and post-displacement time of workers displaced during 2009-2011. When income loss between $t-3$ and $t+2$ is compared, ICT workers have suffered more percentage-wise (8.3% loss) than non-ICT workers (7.6% loss), but when income changes are compared between $t-1$ and $t+2$, non-ICT workers (8.2% loss) have suffered more than ICT workers (5.9% loss). In terms of other time periods, the evidence varies. During displacement periods 1998-2000 and 2005-2007, ICT workers suffer more in terms of income changes both between $t-3$ and $t+2$, and between $t-1$ and $t+2$, while for displacement period 1991-1993 the situation is exactly the opposite. In monetary terms, ICT employees lose more than non-ICT employees during all other time periods except the recession period of 1991-1993. This is perhaps not a surprise, since their initial average income level is significantly larger, meaning that a drop to zero leads to larger loss in monetary terms.

I decided not to control for previous incomes in my main results, but as a comparison, I include a version for displacement period 2009-2011 that controls for income of pre-displacement years t, $t-1$ and $t-2$ (*Table 5*). In this case, the estimated effect of job loss on earnings is considerably smaller for both ICT workers and non-ICT workers. Estimates suggest that two years after job loss that happened during 2009-2011, displaced ICT workers have 9.3% lower earnings, and displaced non-ICT workers 8.9% lower earnings compared to their counterparts. When looking at pre-displacement characteristics of $t-3$, displaced non-ICT workers are still negatively selected with 0.9% lower earnings, while displaced ICT workers are slightly positively selected with 0.1% higher earnings. The former estimate is statistically significant (1% level), while the latter one is not.

Table 5: Regression estimates of ICT sector income losses after job loss in 2009-2011

	t-2	*t-1*	*t*	*t+1*	*t+2*	*t+3*	*t+4*
Main estimate of earned income	-0.108***	-0.117***	-0.105***	-0.114***	-0.176***	-0.142***	-0.119***
Estimate with controlled past income	0	0	0	-0.020	-0.093***	-0.067**	-0.050**
N	*152,111*	*152,111*	*152,111*	*151,308*	*150,460*	*149,728*	*149,155*

First row presents results for outcome variable earned income, measured as monetary annual earnings, and second row for outcome variable earned income, when controls include previous income of periods t, $t-1$ and $t-2$. The latter estimates are divided by mean income values to obtain differences in percentages. N refers to the number of observations. Stars indicate significance, at 10% (*), 5% (**) and 1% (***) level.

In order to obtain more insight on the actual monetary losses of job displacement, I add an additional outcome measure of *all income* as a comparison. Especially in Finland, unemployment does not mean an income drop to zero, but the person is entitled to various social benefits depending on the situation in question. Due to limited information on non-taxable income and a limit of minimum taxable amount of 16,900 euros annual income in state taxation (see *footnote 7* for more detail), this measure contains errors. The measure is mostly erroneous for low income individuals (i.e. those earning less than 16,900 per year and those entitled to non-taxable social benefits), and therefore it is likely to overestimate the actual amount of monetary losses of job displacement. Also, this measure includes capital income, therefore providing a more complete picture of the financial differences among displaced and non-displaced.

Table 6: Regression estimates of income losses after job loss in 2009-2011

	t-2	*t-1*	*t*	*t+1*	*t+2*	*t+3*	*t+4*
ICT displaced:							
All income	-0.110***	-0.121***	-0.110***	-0.117***	-0.150***	-0.128***	-0.171**
Earned income	-0.108***	-0.117***	-0.105***	-0.114***	-0.176***	-0.142***	-0.119***
Difference	*-0.0012*	*-0.0041*	*-0.0049*	*-0.0036*	*0.0259*	*0.0139*	*-0.0520*
Non-ICT displaced:							
All income	-0.029***	-0.032***	-0.024***	-0.048***	-0.074***	-0.072***	-0.062***
Earned income	-0.039***	-0.034***	-0.035***	-0.075***	-0.116***	-0.100***	-0.087***
Difference	*0.0104*	*0.0019*	*0.0112*	*0.0271*	*0.0425*	*0.0280*	*0.0250*

Table 5 presents the regression estimates of effect of job loss on all income and earned income, separately for displaced ICT workers and displaced non-ICT workers. Stars indicate significance, at 10% (*), 5% (**) and 1% (***) level.

For displaced non-ICT workers, the negative effects on earnings are larger in terms of earned income than in terms of all income. Losses in all income are around 2-4 percentage points lower than losses in earned income. This finding is in line with what I expected, since if displaced and non-displaced are somewhat similar in terms of capital income, presumably higher social benefits received by displaced should offset part of the losses in earned income. However, when comparing the differences in effects of displaced ICT workers, the situation is almost the opposite. Displaced ICT workers suffer more in terms of all income during all other observation years except $t + 2$ and $t + 3$. This suggests that a presumptive increase in social benefits of displaced ICT workers does not cover their lower level of capital income compared to non-displaced ICT workers.

5.3. Effect on probability of becoming an entrepreneur

This section estimates the differences in the probability to become an entrepreneur between displaced and non-displaced workers. Displacement does not seem to considerably increase the probability of becoming entrepreneur. My results suggest increased, but rather small probability of becoming an entrepreneur after displacement. Displaced employees have 0.3-0.5 percentage points higher probability of becoming an entrepreneur, compared to non-displaced, during the first two years after displacement that happened during 2009-2011 or 2005-2007. After more than four years of job loss, displaced workers are 0.6-0.7 percentage points more likely to be entrepreneurs.

Employees displaced during more recent time periods were also 0.2-0.3 percentage points more likely to be entrepreneurs also prior their displacement. *Table 7* presents the results.

Table 7: Effect of job loss on the probability of becoming self-employed

	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5
09-11 Non-ICT displ.	0.003***	0.002***	0	0.003***	0.004***	0.005***	0.006***	0.006***
09-11 ICT displ.	0.001	0.001	0	0.004**	0.004	0.005	0.006	0.006
N	*2,282,304*	*2,282,304*		*2,276,481*	*2,270,590*	*2,264,936*	*2,259,224*	*1,493,956*
05-07 Non-ICT displ.	0.003***	0.002***	0	0.003***	0.005***	0.005***	0.006***	0.006***
05-07 ICT displ.	0.000	0.000	0	0.001	0.003	0.003	0.004	0.003
N	*1,976,500*	*1,976,500*		*1,971,029*	*1,965,886*	*1,961,112*	*1,956,467*	*1,951,459*
98-00 Non-ICT displ.	0.000	0.000	0	0.001	0.001**	0.001**	0.002***	0.002***
98-00 ICT displ.	0.004	0.004	0	0.001	0.001	0.003	0.004	0.005*
N	*1,950,188*	*1,950,188*		*1,944,945*	*1,939,580*	*1,934,629*	*1,929,841*	*1,925,052*
91-93 Non-ICT displ.	0.002***	0.001***	0	0.004***	0.007***	0.010***	0.013***	0.014***
91-93 ICT displ.	0.000	0.000	0	0.005***	0.009***	0.011***	0.012***	0.012***
N	*2,088,388*	*2,088,388*		*2,083,687*	*2,078,551*	*2,072,903*	*2,066,989*	*2,060,690*

Table presents the difference in the probabilities to become an entrepreneur between displaced and non-displaced workers. Time t refers to displacement year. Employees are conditioned to be non-entrepreneurs at time t and employed at time t, $t-1$ and $t-2$. Number of observations is the same for t, $t-1$ and $t-2$. For observation period 2009-2011, number of observations drops dramatically after $t+4$, since the data set provides information of 2011 displaced only until $t+4$. Stars indicate significance, at 10% (*), 5% (**) and 1% (***) level.

Coefficients are positive for both, displaced ICT employees and displaced non-ICT employees, although there does not seem to be much difference between the two groups. Coefficients for interaction term *displaced*ICT* are positive, but insignificant, during the first years after displacement for all time periods except 2005-2007. For displacement period 2005-2007, the estimates are negative for all years following displacement, but statistically significant only for $t + 1$ (estimate: -0.002), $t + 6$ (-0.005), $t + 7$ (-0.005) and $t + 8$ (-0.006). This suggests that there are no large differences in the probability of becoming an entrepreneur between displaced ICT workers and displaced non-ICT workers.

5.4. *Effects on probability of staying in the ICT sector*

As my last outcome variable, I explore the effects of job loss on the probability of staying in the ICT sector. Since employee's industry is defined based on her employer's industry, only employed persons have an industry in the data set. Therefore, employment level needs to be taken into consideration when interpreting the regression results of this section. I subtract the displacement effect of employment from the regression results to obtain the actual number of those who were initially working for ICT sector, but afterwards *employed* in another sector. *Table 8* presents the results.

After adding the effect of employment, the only time period providing statistically significant results at $t + 1$ and $t + 2$ is 2009-2011. The magnitude of the probability of leaving ICT sector has increased over time, perhaps indicating of higher willingness to change one's sector when needed. Employees displaced during 2009-2011 were 9.8 percentage points more likely to leave ICT sector compared to non-displaced at year $t + 1$, while the difference in the same likelihood was 3.5 percentage points for employees displaced during 1991-1993. However, when more years have passed after the displacement, employees displaced during earlier periods are less likely to return to ICT sector, while most of the workers displaced during more recent periods are returning to the ICT sector.

Table 8: Effects of job loss on the probability to stay in ICT sector

	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6
09-11 displ.	-0.063*	-0.039	0	-0.098**	-0.116***	-0.155***	-0.156	-0.13**	-0.052
	(0.037)	(0.039)		(0.041)	(0.044)	(0.049)	(0.049)	(0.052)	(0.053)
N	*152,111*	*152,111*		*151,308*	*150,460*	*149,728*	*149,155*	*99,937*	*49,297*
05-07 displ.	0.039***	0.005	0	-0.059	-0.079*	-0.017	-0.028	-0.022	-0.014
	(0.011)	(0.010)		(0.041)	(0.041)	(0.040)	(0.037)	(0.035)	(0.035)
N	*188,428*	*188,428*		*187,451*	*186,653*	*186,090*	*185,611*	*185,131*	*184,620*
98-00 displ.	-0.017	-0.023	0	-0.075*	-0.062	-0.067	-0.069	-0.074	-0.054
	(0.027)	(0.026)		(0.041)	(0.043)	(0.043)	(0.050)	(0.051)	(0.047)
N	*139,687*	*139,687*		*138,910*	*138,282*	*137,929*	*137,705*	*137,508*	*137,253*
91-93 displ.	-0.032	-0.065	0	-0.035	-0.060	-0.059	-0.047	-0.136***	-0.153***
	(0.048)	(0.054)		(0.027)	(0.042)	(0.036)	(0.037)	(0.042)	(0.042)
N	*106,669*	*106,669*		*106,385*	*106,072*	*105,755*	*105,467*	*105,171*	*104,848*

Table 7 presents estimated difference between displaced ICT and non-displaced ICT employees' probability to continue working in the ICT sector. Time t refers to corresponding year of job loss. Employees are conditioned to be working in ICT sector at time t. Values $t-1$ and $t-2$ show the difference prior to the displacement, while $t+1$, $t+2$, …, $t+6$ present the difference after the displacement. Employment level difference is subtracted from the regression results. This means that the values present the estimated difference between those who are employed. Unemployed workers are excluded from the analysis, since they do not have an industry in the data set. Number of observations is the same for t, $t-1$ and $t-2$. For observation period 2009-2011, number of observations drops dramatically after $t+4$, since the data set provides information of 2011 displaced only until $t+4$. Standard errors are in parentheses. Stars indicate significance, at 10% (*), 5% (**) and 1% (***) level.

As ICT sector definition is different from other industry definitions applied by Statistics Finland (and a mixture of several industries), there is no clear way to establish other, comparable sectors. Other sectors vary substantially in size and are less-specific in terms of their contents. In addition to that, classifications have varied over time considerably more among other sectors than ICT. Therefore, comparisons of the likelihood of individuals to change a sector after job loss, in a case when their initial sector was other than ICT, would have been mostly artificial. Nevertheless, this means that I cannot conclude whether the probability to leave or stay in the ICT sector is relatively large or not.

6. Conclusions

This Master's Thesis explores the effects of job loss on various labor market outcomes of displaced ICT workers, using plant closures and mass lay-offs as exogenous shocks. My outcome variables of interest are change in employment level, change in earnings, change in the probability of becoming an entrepreneur and change in the probability of staying in the ICT sector after job loss.

I find no statistically significant differences in the effects of job loss on employment level between displaced ICT workers and displaced non-ICT workers. In terms of effects on earnings, the differences are statistically significant across all time periods. However, the evidence varies across time. My results suggest larger losses in income for ICT workers compared to non-ICT workers for the three most recent time periods, but larger losses for non-ICT workers for the recession period of 1991-1993. ICT workers displaced during 2009-2011 experience 11.4% loss in earned income one year after displacement and 17.6% loss two years after displacement, compared to non-displaced ICT workers. For other displaced workers, the losses are 7.5% and 11.6% for $t+1$ and $t+2$, respectively.

Job displacement seems to induce only a rather small increase of 0.1-0.7 percentage points in the probability of becoming an entrepreneur. There are no statistically significant differences between displaced ICT workers and other displaced workers. My last outcome variable of interest, probability of staying in ICT sector, is around ten percentage points lower for workers displaced in 2009-2011, compared to non-displaced workers. Also this effect has varied over time, suggesting higher estimates for more recent years. This finding indicates of perhaps higher willingness to move to another sector in case of job loss.

7. References

Adda, J., Dustmann, C., & Stevens, K. (2017). The Career Costs of Children. *Journal of Political Economy*, *125*(2), 293–337.

Addison, J. T., & Portugal, P. (1989). Job Displacement, Relative Wage Changes, and Duration of Unemployment. *Journal of Labor Economics*, *7*(3), 281–302.

Cahuc, P., Carcillo, S., & Zylberberg, A. (2014). *Labor Economics* (Second Edition). The MIT Press.

Eliason, M., & Storrie, D. (2006). Lasting or Latent Scars? Swedish Evidence on the Long-Term Effects of Job Displacement. *Journal of Labor Economics*, *24*(4), 831–856.

Handwerker, E. W., & von Wachter, T. (2010). Variation in the Cost of Job Loss by Worker Skill: Evidence Using Matched Data from California, 1991-2000. *Discussion Paper Series, Columbia University*.

Huttunen, K., & Kellokumpu, J. (2016). The Effect of Job Displacement on Couples' Fertility Decisions. *Journal of Labor Economics*, *34*(2), 403–442.

Kletzer, L. G. (1998). Job Displacement. *The Journal of Economic Perspectives*, *12*(1), 115–136.

McCall, J. J. (1970). Economics of Information and Job Search. *The Quarterly Journal of Economics, 84*(1), 113-126.

Mortensen, D. T. (1970). Job Search, the Duration of Unemployment, and the Phillips Curve. *The American Economic Review, 60*(5), 847-862.

Pohjola, M. (2014). *Suomi uuteen nousuun – ICT ja digitalisaatio tuottavuuden ja talouskasvun lähteinä*. Teknologiateollisuus ry:n julkaisema raportti.

Statistics Finland websites of patenting, ICT sector and detailed industry classifications (Accessed on 25th October, 2017):

http://www.stat.fi/til/pat/2006/pat_2006_2007-10-25_kat_003_en.html

http://www.stat.fi/meta/kas/ict_sektori.html

http://www.stat.fi/meta/luokitukset/toimiala/001-2008/268.html

Stevens, A. H. (1997). Persistent Effects of Job Displacement : The Importance of Multiple Job Losses. *Journal of Labor Economics*, *15*(1), 165–188.

Sullivan, D., & von Wachter, T. (2009). Job Displacement and Mortality: An Analysis using Administrative data. *The Quarterly Journal of Economics*, *124*(3), 1265–1306.

Topel, R. (1990). Specific Capital and Unemployment: Measuring the Costs and Consequences of Job Loss. *Carnegie-Rochester Conference Series on Public Policy*, *33*, 181–214.

8. Appendices

Appendix A: Industry Classifications

Statistics Finland industry classifications available at:
http://www.stat.fi/meta/luokitukset/index.html

Definition of ICT sector. This classification is used in the data for years 2007-2014

261	Manufacture of electronic components and boards
262	Manufacture of computers and peripheral equipment
263	Manufacture of communication equipment
264	Manufacture of consumer electronics
268	Manufacture of magnetic and optical media
4651	Wholesale of computers, computer peripheral equipment and software
4652	Wholesale of electronic and telecommunications equipment and parts
582	Software publishing
61	Telecommunications
62	Computer programming, consultancy and related activities
631	Data processing, hosting and related activities; web portals
951	Repair of computers and communication equipment

Industry classifications for 2002 (TOL2002) are used in the data for 2001-2006. Industry classifications for 1995 are used in the data for 1988-2000. The following list shows the content of these classifications. They both followed OECD classifications from year 1999.

3001	Konttorikoneiden valmistus
3002	Tietokoneiden ja muiden tietojenkäsittelylaitteiden valmistus
3130	Eristettyjen johtimien ja kaapelien valmistus
3210	Elektronisten piirien ja muiden elektronisten osien valmistus
3220	Televisio- ja radiolähettimien sekä lankapuhelin- ja -lennätinlaitteiden valmistus
3230	Televisio- ja radiovastaanottimien, äänen- ja kuvantallennus- ja -toistolaitteiden valmistus
3320	Mittaus-, tarkkailu- ja navigointilaitteiden yms. valmistus
3330	Teollisuuden prosessinsäätölaitteiden valmistus
51432	Viihde-elektroniikan tukkukauppa
51840	Tietokoneiden, oheislaitteiden ja ohjelmistojen tukkukauppa (TOL 1995:51641 Tietokonelaitteistojen tukkukauppa)
51862	Tietoliikennevälineiden tukkukauppa (TOL 1995: 51652)
642	Teleliikenne
7133	Konttorikoneiden jne. vuokraus
72	Tietojenkäsittelypalvelu

Appendix B: Descriptive statistics by displacement year.

1) Characteristics of displaced and non-displaced in total sample.

	2009-2011			2005-2007		
	Displaced	*Non-displaced*	*Difference*	*Displaced*	*Non-displaced*	*Difference*
Age	40.01	41.21	*-1.193****	40.13	40.73	*-0.594****
Male	0.46	0.49	*-0.031****	0.44	0.54	*-0.094****
ICT sector	0.04	0.06	*-0.024****	0.11	0.09	*0.022****
Earned income	33262	39001	*-5739****	31204	38252	*-7048****
All income	35901	41442	*-5541****	33990	41076	*-7086****
Plant size	318	435	*-117****	388	441	*-53****
Education level	3.71	3.99	*-0.273****	3.60	3.67	*-0.076****
Married	0.46	0.51	*-0.046****	0.49	0.51	*-0.024****
Private sector	0.52	0.60	*-0.076****	0.47	0.70	*-0.223****
Foreign language	0.05	0.03	*0.011****	0.03	0.02	*0.005****
Observations	*137,609*	*2,510,873*		*116,449*	*2,203,741*	

	1998-2000			1991-1993		
	Displaced	*Non-displaced*	*Difference*	*Displaced*	*Non-displaced*	*Difference*
Age	39.69	40.33	*-0.640****	38.32	39.17	*-0.849****
Male	0.40	0.52	*-0.128****	0.58	0.52	*0.064****
ICT sector	0.07	0.07	*-0.007****	0.05	0.05	*0.005****
Earned income	28289	32961	*-4673****	27421	29159	*-1739****
All income	31263	35376	*-4113****	29340	30857	*-1517****
Plant size	353	500	*-148****	230	530	*-300****
Education level	3.41	3.40	*0.003*	2.59	2.91	*-0.318****
Married	0.50	0.56	*-0.065****	0.56	0.60	*-0.042****
Private sector	0.35	0.58	*-0.239****	0.69	0.50	*0.194****
Foreign language	0.02	0.01	*0.008****	0.01	0.01	*0.001****
Observations	*89,903*	*2,262,794*		*145,350*	*2,220,512*	

Time period refers to displacement year. Stars indicate significance, at 10% (*), 5% (**) and 1% (***) level.

2) Characteristics of displaced ICT workers and non-displaced ICT workers during earlier time periods.

	ICT sector displacements 2009-2011			*ICT sector displacements 2005-2007*		
	Displaced	*Nondisplaced*	*Difference*	*Displaced*	*Nondisplaced*	*Difference*
Age	39.26	39.55	*-0.285***	39.06	38.24	*0.823****
Male	0.65	0.69	*-0.038****	0.61	0.66	*-0.050****
Earned income	49056	58964	*-9908****	46742	52970	*-6228****
All income	51035	61591	*-10556****	49466	56315	*-6849****
Plant size	162	615	*-452****	271	624	*-353****
Education level	4.59	4.97	*-0.381****	4.25	4.64	*-0.39****
Married	0.52	0.57	*-0.051****	0.51	0.53	*-0.023****
Foreign language	0.04	0.06	*-0.019****	0.02	0.04	*-0.018****
Observations	*5,350*	*157,347*		*12,799*	*194,661*	

	ICT sector displacements 1998-2000			*ICT sector displacements 1991-1993*		
	Displaced	*Nondisplaced*	*Difference*	*Displaced*	*Nondisplaced*	*Difference*
Age	36.91	36.07	*0.837****	39.83	36.63	*3.194****
Male	0.57	0.61	*-0.039****	0.64	0.60	*0.041****
Earned income	36366	42102	*-5736****	31881	33402	*-1521****
All income	42896	44767	*-1871****	33311	34839	*-1528****
Plant size	354	490	*-136****	161	319	*-158****
Education level	3.82	3.98	*-0.155****	2.82	3.31	*-0.486****
Married	0.48	0.50	*-0.017***	0.63	0.58	*0.055****
Foreign language	0.02	0.01	*0.003***	0.00	0.01	*-0.003****
Observations	*5,944*	*164,750*		*7,799*	*108,480*	

Time period refers to displacement year. Stars indicate significance, at 10% (*), 5% (**) and 1% (***) level.